Cloud Computing: Web-Scale Information Processing with MapReduce

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Thursday, May 29, 2008
HCIL Symposium
“Web-Scale” Problems

- Emergence of data-intensive problems:
  - Problems involving the Web (e.g., crawling, searching)
  - “Post-genomics era” in life sciences
  - Data from accelerator experiments, remote sensors, …
  - Web 2.0 applications
  - High-quality animation

- How can we practically tackle these problems?
How much data?

- CERN’s LHC will generate 15 PB a year (2008)
- NOAA has ~1 PB climate data (2007)
- Wayback machine has ~2 PB (2006)
- Google processes 20 PB a day (2008)
- “all words ever spoken by human beings” ~ 5 EB

640K ought to be enough for anybody.
**Relevance to HCI**

- What does this have to do with HCI?
- Interfaces lies at the end of a long data analysis pipeline:
  - Collection, storage (by machines)
  - Aggregation, filtering, reduction (by machines)
  - Visualization, analysis, manipulation (by humans)

Humans can’t interact with what machines can’t crunch!
Only Practical Solution (Today)

- Divide and conquer
- Throw more machines at it

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[Diagram showing a hierarchical process with 'Work' at the top, partitioned into 'w1', 'w2', 'w3' which are further divided into 'worker' nodes 'r1', 'r2', 'r3'. The 'r1', 'r2', 'r3' nodes are connected to a 'Result' node.]
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Challenges for Scaling Up

- Issues in parallel and distributed processing
  - Scheduling, data distribution, synchronization, …
  - Robustness, fault tolerance, …
- Traditional models for parallel and distributed programming are hard!

![Message Passing Diagram](image)

![Shared Memory Diagram](image)
MapReduce in a Nutshell

- General problem structure:
  - Iterate over a large number of records
  - Extract something of interest from each
  - Shuffle and sort intermediate results
  - Aggregate intermediate results
  - Generate final output

- MapReduce provides a functional abstraction:
  - Programmer supplies “Mapper” and “Reducer”
  - Runtime automatically handles everything else!

- MapReduce deployments:
  - Google processes 20 PB a day with proprietary implementation in C++
  - Hadoop is an open-source reimplementation in Java
MapReduce Runtime

- Handles scheduling
  - Assigns workers to map and reduce tasks
- Handles data distribution
  - Gets map workers to the data
- Handles synchronization
  - Shuffles data from mappers to reducers
- Handles faults
  - Detects worker failures and restarts
- Everything happens on top of distributed FS
  - GFS = Google File System
“Cloud Computing” Initiative

- Google/IBM’s academic cloud computing initiative (October 2007)
  - Six initial pilot institutions: Washington, Berkeley, CMU, MIT, Stanford, UMD

- IBM provides UMD a Hadoop cluster
  - 20 machines (40 processors)
  - Couple of TB storage
  - Associated infrastructure support

- Maryland does good work with the cluster!
  - Use it to tackle open research problems
  - Use it in the classroom
Cloud Computing Course

- Attempt at integrating teaching and research
  - Pilot course in Spring 2008
  - Basic idea: Ph.D. students leading teams of masters and undergraduate students
  - Goal: tackle “Web-scale” research problems
  - Evaluation: generate publishable results

- What do students get out of it?
  - Everyone learns about MapReduce
  - Undergraduates learn about a particular research area
  - Ph.D. students gain mentoring experience (and help with their work)
Ongoing Projects

- Six teams:
  - Statistical machine translation
  - Reference resolution in email archives
  - Language modeling
  - Biomedical text retrieval
  - Text-image separation in children’s books
  - Biological sequence alignment

- Thirteen students
  - 3 undergrads, 3 Masters, 7 Ph.D.
  - From the iSchool, CS, Linguistics, Geography

- Many campus labs involved
  - NLP/IR, HCI, computational biology, etc.
Statistical Machine Translation

Chris Dyer (Ph.D. student, Linguistics)
Aaron Cordova (undergraduate, Computer Science)
Alex Mont (undergraduate, Computer Science)

- Conceptually simple:
  (translation from foreign $f$ into English $e$)
  \[
  \hat{e} = \arg \max_e P(e \mid f)
  \]
  \[
  \hat{e} = \arg \max_e P(f \mid e)P(e)
  \]

- Difficult in practice!

- Phrase-Based Machine Translation (PBMT):
  - Break up source sentence into little pieces (phrases)
  - Translate each phrase individually
Phrasal Decomposition

Example from Callison-Burch (2007)
MT Architecture

Training Data

i saw the small table
vi la mesa pequeña

Parallel Sentences

he sat at the table
the service was good

Target-Language Text

maria no daba una bofetada a la bruja verde

Foreign Input Sentence

Word Alignment

(vi, i saw)
(la mesa pequeña, the small table)

Phrase Extraction

Language Model

Translation Model

Decoder

mary did not slap the green witch

English Output Sentence
Image Processing

Chang Hu (Ph.D. student, Computer Science),
Punit Mehta (undergraduate, Computer Science)

- Text-image separation in children’s books
  - International Children’s Digital Library (ICDL):
    2412 books, 155,962 pages (and counting)

- Hand transcription to improve readability

- Successful implementation in Hadoop
  - Takes advantage of distributed file system
Want to learn more?

- Come to my tutorial tomorrow!
- Topics covered:
  - Overview of parallel and distributed computing
  - Functional programming
  - MapReduce and the Google File System
  - Graph Algorithms with MapReduce
  - Information Retrieval Algorithms with MapReduce
Acknowledgements

- **Google:** Christophe Bisciglia, et al.
- **IBM:** Dennis Quan, Eugene Hung, et al.
- Thirteen bright students from UMD:

  - Chris Dyer (Linguistics Ph.D.)
  - Tamer Elsayed (CS Ph.D.)
  - Alex Mont (CS ugrad)
  - Greg Jablonski (iSchool masters)
  - Aaron Cordova (CS ugrad)
  - Alan Jackoway (CS ugrad)
  - Chang Hu (CS Ph.D.)
  - Denis Filimonov (Linguistics Ph.D.)
  - Punit Mehta (iSchool masters)
  - Hua Wei (Geography Ph.D.)
  - George Caragea (CS Ph.D.)
  - Mike Schatz (CS Ph.D.)
  - Christians Camacho (iSchool masters)